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A deep neural network-based strategy for recommending online teaching resources for ideological and political theory courses

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ABSTRACT

With the development of the informationization era, it has become the norm for teachers of Civics and Political Science courses in colleges and universities to assist classroom teaching through network resources. In order to further utilize network resources to make them better serve the classroom teaching of Civics and Politics courses in colleges and universities, this paper optimizes the teaching resources recommendation technology based on deep neural network. Defining the network teaching resources data as a ternary group $A=(U,I,C)$, we put forward the research hypothesis and LSTM model, and establish the G-LSTM recommendation model for recommending the teaching resources of ideological network. The overall framework of G-LSTM model is described, and the recommendation based on G-LSTM is applied to the ideological network teaching resources recommendation. Adopt AUC, MRR and NDCG as evaluation indexes to check the performance indexes of G-LSTM model. Combined with the actual teaching of ideologic theory class, the practical effect of G-LSTM recommendation model is analyzed. 67.81% of students and 39.71% of teachers recognize each recommended online teaching resources. It shows that the improved LSTM model in this paper can further screen the ideological and political network teaching resources, and the teaching resources recommended by the model are more suitable for the teaching of ideological and political theory.

Keywords: LSTM model; teaching resources recommendation; NDCG; ideological and political theory class

1. Introduction

Under the background of new engineering construction and education big data, teaching resources show explosive growth, and its characteristics of fast updating and complex correlation between knowledge points bring problems of information overload and learning disorientation [1-2]. The construction and optimization of teaching resources is a necessary way to improve the quality of teaching and students' learning effect, which can not only provide teachers with diversified teaching materials and promote

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teaching innovation, but also enrich students' learning experience, cultivate their in-depth understanding, and satisfy their personalized learning needs [3-5].

In order to select high-quality teaching resources efficiently and quickly, existing research has been mainly realized by designing rational and advanced teaching resource recommendation methods [6]. However, during the development and optimization of teaching resources recommendation system, the algorithms and models are constantly improving, but the recommendation strategy still stays in the two aspects of user preference analysis or content relevance computation, ignoring the role of teachers' control of teaching objectives and the practical guidance of enterprise mentors in teaching resources recommendation [7]. A good teaching resource should not only be related to the knowledge points and cater to the learning habits and preferences of students, but also be in line with the positioning of teachers' teaching objectives, and should consider the employment practice and social development needs in advance [8-9].

In the context of the construction of the Civics Education Resource Base, teachers can collect and analyze teaching-related data through the scientific and reasonable application of the Civics Teaching Resource Recommendation Method, which can enhance the teaching effect of the Civics courses to a certain extent and enrich the learning experience of the students. In the vast amount of Civics teaching resources data, by quickly and effectively extracting the demand data, the students' political literacy can be improved, so that they can accurately choose the learning content suitable for them [10]. In order to better meet students' individualized needs and improve the efficiency and effectiveness of Civics teaching resources, the application of recommendation methods in Civics teaching resources has gradually become a hot spot of research [11]. However, the research and practice of recommendation methods for Civics teaching resources still face many challenges, and the problems of how to accurately capture students' interests and needs, ensure the authenticity and reliability of recommended resources, and improve the scalability and accuracy of recommendation methods have been troubling researchers [12].

High-quality teaching resources recommendation can accurately understand the needs of learners, fully consider the differences of learners and the similarity of content, so as to provide personalized and diversified teaching resources, and enhance the sense of students' learning experience. Literature [13] conceptualized a hybrid course recommendation system for online learning platforms, the underlying logic of the recommendation system is based on the integration of collaborative filtering and content-based recommendation, and the good performance of the recommendation system is confirmed through simulation experiments. Literature [14] systematically analyzes the current recommendation learning mode of e-learning. Literature [15] reviewed the literature studies related to learning analytics reporting system, including the development process and products of learning analytics reporting system, and evaluated how learning analytics reporting system affects students' learning behaviors and academic performance through teaching experiments. Literature [16] developed a PLRS architecture based on an existing telecommunication recommender system to support students' learning material retrieval through a learning management system, and also built a collaborative dataset that can be targeted to recommend learning materials from previous top students. Literature [17] examined the fairness of learning recommender system based on collaborative filtering strategy, pointed out that there is a lack of fairness in this type of learning recommender system, and established a new fairness index to optimize the recommender system, and examined the comprehensive dataset did not formally proposed new index optimization scheme, which effectively improves the fairness of learning recommender system based on collaborative filtering strategy. Literature [18] reviewed the recommendation system with reinforcement learning policy as the core, and looked forward to the future research development path and potential in the field of user recommendation, analyzing the algorithm selection of the recommendation system through an RLRS framework covering the dimensions of state representation, policy optimization, reward formulation and environment construction. Literature [19] attempted to identify student engagement in Open University (OU) social science courses based on machine learning algorithms, and then assessed how VLE course engagement affects students' academic performance and learning behaviors, etc., based on which a dashboard tool was developed to assist instructors in mastering students' VLE course engagement. Literature [20] established an intelligent teaching big data platform, which can realize the tracking and analysis of students' learning progress and assist teachers in mastering students' learning dynamics and situation, as well as help students screen learning resources and give students scientific recommendations of previous excellent students' learning resources, in order to help students learn in a targeted way and improve their learning performance.

Under the background of big data economy, the network teaching of ideological theory class in higher vocational colleges and universities must integrate more resources, and many educational types of enterprises rely on the integration and sale of educational resources to obtain benefits, so it can be seen that carrying out network teaching has become a new educational economic model, and network teaching of ideological and political theory in higher vocational colleges and universities can also realize the win-win situation of educational benefits, social benefits and economic benefits. Literature [21] describes the wireless network, the Internet and other technologies to empower the work of ideology and politics. Literature [22] clarifies the real obstacles existing in the current civic education network, and gives targeted solutions to effectively enhance the attractiveness of civic education for students, and strengthen the influence and dissemination of civic education in social networks, and promote the effect of civic education network teaching to improve. Literature [23] builds an analytical model of political belief and political attitude management, and combines relevant panel data to carry out experimental investigation, and the study confirms that symbolic politics promotes the integration of belief systems and motivational behaviors in the process of symbolic politics plays a positive role, and the study further deepens the association between political belief systems and network science. Literature [24] elaborated on the new modes and methods of education brought about by the cloud platform technology-enabled civic education, and emphasized that cloud computing technology-enabled civic network education in colleges and universities has brought about important innovations and practical significance in the field of civic education, and concluded that there is a need for further in-depth research into the optimization of the functions and innovation of the teaching strategies of cloud computing-based civic education. Literature [25] used a questionnaire survey method to investigate how network technology affects the ideological and political education of students in colleges and universities, and the results of the survey found that while network technology promotes the innovation of political education and the improvement of college students' ability, it also exists obstacles such as the lack of teaching personality and the imperfection of the construction of the platform of ideologic network education.

This paper analyzes the main modes of network teaching of ideological and political theory courses in colleges and universities at present, defines network teaching, and divides the network teaching resources of ideological theory courses. It analyzes the necessity of utilizing network resources for classroom teaching of ideological and political courses in colleges and universities. Introducing the recommendation method based on deep neural network, on the basis of LSTM model, integrating the generalized matrix decomposition module and the long and short memory network module, improving the LSTM model, and proposing the recommendation algorithm of network teaching resources based on G-LSTM. A dataset of network teaching resources in the field of ideology and politics is established to compare the performance indexes of each recommendation algorithm and analyze the construction and application of network teaching resources in ideology and politics.

2. Development of online teaching resources for ideological and political theory courses

2.1. *Content and Main Modes of Online Teaching in Ideological and Political Theory Courses*

Specifically, the current network teaching mode of ideological and political theory course in colleges and universities has the following modes:

1) Establishing a systematic website with the theme of ideological and political theory course

2) Combination of multimedia-assisted teaching, classroom and network
3) Teachers and students to build a virtual ideological and political theory classroom on the Internet

2.2. *Definition of online teaching resources for ideological and political theory courses*

Network teaching refers to the guidance of modern educational thinking and learning theory, giving full play to the educational function of the network and the advantages of educational resources [26-27]. Ideological and political theory course network teaching resources can be divided into hardware environment resources, network information resources and teaching human resources.

2.3. *The Necessity of Utilizing Network Resources for Classroom Teaching of Ideological and Political Theory Courses*

2.3.1. Meeting the need to expand classroom capacity. The nature of the discipline of the Civics and Political Science course in colleges and universities determines that the course itself is serious, but this by no means means means that the Civics and Political Science course is obscure, difficult to understand, boring and uninteresting.

2.3.2. Meeting the needs of contemporary university students. In the current situation, in the face of college students as a "new generation of network", the use of network resources in the classroom teaching of college and university civics is undoubtedly a "grounded" "effective intervention in the students to play something It is a concrete manifestation of "effectively intervening in what students play".

The introduction of "grounded" network resources, the ideological theory from "loyalty to the ear" to "loyalty to the ear", can reduce the communication barriers between the teachers of the political class and students. It creates a relaxing and pleasant learning atmosphere, which makes students have good interest in learning and improves their learning results.

2.3.3. Responding to the challenges of negative information on the Internet. Teachers of ideology and politics class utilize network resources from both positive and negative sides, reflecting the objective facts comprehensively instead of deliberately obscuring them, which is conducive to guiding college students to learn to compare, choose and judge in the value conflict, so as to enable them to set up a correct value system of thought.

2.4. *Recommendation Technology of Online Teaching Resources for Thought and Political Theory Courses*

2.4.1. Deep Neural Network Based Recommender System. Deep neural networks can fit complex relationships in the data through simple linear variations between its many neurons between layers [28].

The neural network based recommendation system first extracts the user as well as item extraction to get the user feature vector and item feature vector. The extracted user feature vectors and item feature vectors are then pairwise fed into a neural network model to train the neural network model. If there is an interaction between the user represented by the user vector and the item represented by the item vector, the desired output of the neural network is set to 1 and vice versa.

After training, all user-item combinations other than the training set are traversed and fed into the trained neural network, and for each user, the top N results with the highest outputs are taken and the items corresponding to these results are recommended to the user.

2.4.2. Recommendation of online teaching resources based on G-LSTM:
1) The key to LSTM is that the transmission of information can run up the chain without any other information affecting the conveyor belt, thus keeping the information constant during transportation.

Another feature of the LSTM model is the addition of many "switches", or "gates", through which information can be increased or decreased. In other words, the "gates" decide whether some information will stay or go.

LSTM model structure analysis

(1) LSTM forgetting gate: Since a large amount of information cannot be all needed, the LSTM model contains a forgetting gate, which means that some useless information is removed, so the function of this gate is to select the forgotten information.

$$f_t = \sigma\left(W_f h_{t-1} + U_f x_t + b_f\right) \tag{1}$$

(2) Input gate of LSTM: Input gate is also what information is input to bring into other layers, which consists of two parts.

$$i_t = \sigma\left(W_i h_{t-1} + U_i x_t + b_i\right) \tag{2}$$

$$\tilde{C}_t = \tanh\left(W_c h_{t-1} + U_C x_t + b_C\right) \tag{3}$$

(3) Cell state update for LSTM

There is another step of cell state update before outputting the information, the result of the information through the forgetting gate and the input gate will act on the cell state C_t, and the cell state update is to see how to get C_t from the cell state C_{t-1}.

$$C_t = f_t * C_t + i_t * \tilde{C}_t \tag{4}$$

(4) Output gate for LSTM

Ultimately, it needs to be determined what value to output, and this output will be based on the cell states in this paper.

$$O_t = \sigma\left(W_o h_{t-1} + U_o x_t + b_o\right) \tag{5}$$

$$h_t = O_t * \tanh\left(C_t\right) \tag{6}$$

2) In order to solve the temporal problem and cold-start problem in online teaching resources recommendation, this paper constructs the G-LSTM model, which integrates the generalized matrix decomposition module and the long-short memory network module. The generalized matrix decomposition module, on the other hand, can replace the traditional matrix decomposition to capture the relationship between users and online teaching resources in online teaching resources data to alleviate the cold-start problem. Thus, the recommender system can be made to have better recommendation results.

Web-based teaching resources data can be defined as a triple $A = (U, I, C)$. where set $U = \{u_1, u_2, \ldots u_m\}$ represents the set consisting of all learners. Set $I = \{i_1, i_2, \ldots i_n\}$ represents the set of all Web-based teaching resources, and each element in the set can be represented by a vector of unique heat codes. Set $C = \left\{c_1^1, c_1^2, \ldots c_1^m, c_2^1, c_2^2, \ldots, c_n^m\right\}$ represents the set of records of all learners' interaction behaviors with all web-based teaching resources. Each element in the set is a ternary consisting of a vector representing the learners, a vector representing the online teaching resources and a vector of interactive behavior information. Its form is:

$$\tilde{c} = [t, s, f_1, f_2, f_3, f_4] \tag{7}$$

Where, t indicates that the web-based teaching resource is the first web-based teaching resource that has been interacted with by the learner. s denotes the cumulative learning time of the web-based teaching resource by the learner. f_1 to f_4 denote the four characteristics, respectively.

Define a subset of set C as $C^u = \left\{c_1^u, c_2^u, \ldots c_n^u\right\}$. Then average the dimensions of the third element $\bar{c}$ of all ternary elements in set C^u and denote it as $\bar{c}^u$. With the above calculation results, the learner's latent factor matrix P can be defined as:

$$P=\begin{bmatrix}\overline{c}^{1^T}\\ \overline{c}^{2^T}\\ \cdots\\ \overline{c}^{m}T\end{bmatrix} \tag{8}$$

The latent factor matrix Q for online teaching resources can then be defined as:

$$Q=\begin{bmatrix}\overline{c}_1^T\\ \overline{c}_2^T\\ \cdots\\ \cdots\\ \overline{c_n}\end{bmatrix} \tag{9}$$

By analyzing the data of online teaching resources, the following hypotheses are proposed:

Hypothesis 1: When a learner interacts with a learning resource such as clicking or studying, this paper assumes that this learner is interested in this learning resource.

Hypothesis 2: All learners are interested in learning resources independently of each other.

Assumption 3: This paper assumes that when a learner is interested in a learning resource, this learner has an implicit connection with this learning resource.

Based on these assumptions, the following definitions are made:

When a learner is interested in a learning resource, the value of the element corresponding to the row representing the learner and the column representing the learning resource in the matrix is R, and vice versa.

Based on the above assumptions and definitions, this paper proposes a G-LSTM recommendation model for online teaching resources recommendation, and its model framework is as follows:

The model as a whole can be defined as:

$$\hat{y}_{ui}=f\left(P^T v_u^U, Q^T v_i^I \middle| \Theta f\right) \tag{10}$$

The input layer of the G-LSTM model consists of a learner vector v_u^U representing the learners and a web teaching resource vector v_i^I representing the web teaching resources.In order to obtain these two vectors, the similarity between all the learners is first calculated. After obtaining the similarity between all the learners and the similarity between all the web-based teaching resources, the learner vector v_u^U representing the learner u can be represented as:

$$v_u^U=\begin{bmatrix}sim(u,u_1)\\ sim(u,u_2)\\ \cdots\\ sim(u,u_m)\end{bmatrix} \tag{11}$$

The web teaching resource vector v_i^I representing web teaching resource i can be denoted as:

$$v_i^I=\begin{bmatrix}sim(i,i_1)\\ sim(i,i_2)\\ \cdots\\ sim(i,i_n)\end{bmatrix} \tag{12}$$

The embedding layer of the G-LSTM model is responsible for mapping the learner vector v_u^U and the online teaching resource vector v_i^I of the two different dimensional input layers into the learner feature vector p_u and the online teaching resource feature vector q_i, respectively. The specific mapping rules are:

$$p_u = P^T v_u^u \tag{13}$$

$$q_i = Q^T v_i^I \tag{14}$$

After the mapping of the embedding layer the dimensions of the learner feature vector and the web teaching resource feature vector become the same value. Here the dimensions of the vectors output from the embedding layer are unified.

The process of GMF module accepting the input from the embedding layer can be expressed as:

$$\hat{y}_{ui}^{GMF} = a_{out}\left(h^T\left(p_u \odot q_i\right)\right) \tag{15}$$

Here a_{out} and h denote the activation function and the edge weights of the GMF module, respectively, and $\odot$ denotes the corresponding multiplication of the congruent elements of the vector.

$$z_1 = g\left(\begin{bmatrix} p_u \\ q_i \end{bmatrix} \middle| \Theta g\right) \tag{16}$$

where Θg represents the model parameters of the long and short-term memory neural network unit. Then the output of $unit_n$ can be represented as:

$$z_n = g\left(z_{n-1} \middle| \Theta g\right) \tag{17}$$

Since there is a total of t long and short term memory neural network unit set up within the LSTM module, the output of the tnd long and short term memory neural network unit is the output of this module, i.e.:

$$\hat{y}_{ui}^{LSTM} = z_t = g\left(z_{t-1} \middle| \Theta g\right) \tag{18}$$

The integration layer of the G-LSTM model is composed of a multilayer perceptron, which is responsible for receiving the predicted value $\hat{y}_{ui}^{GMF}$ output by the GMF module and the predicted value $\hat{y}_{ui}^{LSTM}$ output by the LSTM module, and integrating the two to ultimately output the predicted value of the G-LSTM model as a whole $\hat{y}_{ui}$. $\hat{y}_{ui}$ It can be expressed as:

$$\hat{y}_{ui} = \sigma\left(h^T\begin{bmatrix} \hat{y}_{ui}^{GMF} \\ \hat{y}_{ui}^{LSTM} \end{bmatrix}\right) \tag{19}$$

After obtaining the final output $\hat{y}_{ui}$ of the model, a loss function can be defined:

$$Loss = \sum_{(u,i)\in Y\cup Y^-} w_{ui}\left(y_{ui} - \hat{y}_{ui}\right)^2 \tag{20}$$

where Y represents the set consisting of binary tuples of learners with implicit connections to online teaching resources, $Y-$ represents the set consisting of binary tuples of learners without implicit connections to online teaching resources, and w_{ui} is a hyperparameter representing the training weights of binary tuple (u,i). The parameters of each part of the G-LSTM model are adjusted by minimizing this loss function until the model converges or the training reaches the maximum number of iterations.

3. Recommended Performance of Teaching Resources for Ideological and Political Theory Courses

3.1. *Data sets*

Ideological and political video learning resources require reading data from the online teaching platform and then analyzing and processing the data. The video data are read out and stored in two excel tables. The first table is “video learning data table”, which stores 7125 learning videos. Since the table is too large, only the first ten rows of data are viewed here, and the first ten data of the first table are shown in Table 1.

Table 1. Video learning data sheet

Video ID	Video name	Video category
1	Ideological and political education	Thought politics Teaching
2	Ideological and political class	Thought politics
3	Ideological and political	Thought politics
4	Student thought politics	Thought politics
5	Political science	Thought politics
6	The political department of the university	Thought politics Teaching
7	Ideological and political teaching	Thought politics Teaching
8	Ideological and political teaching resources	Thought politics Teaching
9	Ideological and political major	Thought politics
10	Ideological and political system	Thought politics

The second table is the “Evaluation Scores Table”. It stores 1,580,140,000 evaluation scores with the fields “study number”, “video number” and “rating”. These two tables can also be combined into a single table by using the video number and after reading the data, the rating scores are shown in Table 2.

If the learner has rated the Ideological and political teaching resources highly, then we can try to recommend the video with high similarity to the student. However, if there is a lack of ratings, recommendations can be made through the learner's video viewing behavior. For a learner, the viewing record contains a sequence of several learning videos.

Table 2. Scoring score

Learner ID	Video ID	Scoring
1	3	23
2	6	12
2	12	10
1	66	NULL
1	150	4

3.2. *Performance indicators and comparison methods*

In the recommender system, the representative metrics AUC, MRR and NDCG are selected. NDCG is the Normalized Discounted Cumulative Gain, which evaluates the recommendation lists of different users in a normalized manner. NDCG is an accuracy based metric that measures the distance between the results of the model ranking and the ideal ranking as shown in equation (21). Namely:

$$NDCG_u @ k = \frac{DCG_u @ k}{IDCG_u} \tag{21}$$

Where DCG_u is shown in equation (22). rel_i represents the recommendation result relevance at location i, and u represents the size of the recommendation list. idcg represents the best recommendation result list returned by a particular user, the best DCG. i.e.:

$$DCG_u = \sum_{i=1}^{u} \frac{2^{red} - 1}{\log_2(i+1)} \tag{22}$$

In this paper, we first select the most common recommendation benchmark model: PinSage, and then select two highly competitive CASER and DIN models.

PinSage: is a graph-based recommendation model that generates functional demonstrations for users or items, generally used in large recommender systems for similar item recommendations.

CASER: is a convolutional sequence embedding recommendation model that embeds recent item sequences into temporal and spatial "images", uses convolutional filters to learn sequential patterns as local features of the graph.

DIN: is a deep interest network that adaptively learns a representation of user interests from historical behavior, with expression vectors that vary with different items.

3.3. *Experimental Comparison and Analysis of Results*

Firstly, through collaborative filtering algorithm, the similarity of some videos can be calculated, and big data mining can be used as an example to get the videos related to it. The relevance of ideological videos is shown in Table 3. The learner's rating for the video "College teaching method" is 0.535. NULL means that the learner has not rated the video, and the data table seems to be very sparse.

Table 3. Video correlation

Video name	Correlation coefficient
College teaching method	0.535
Political teacher of thought and politics	0.917
Political celebrity	0.743
Teacher education	NULL
Network video	NULL

Due to the large number of ideological video learning resources, but each student evaluation is limited. So the overall recommendation effect is further tested by combining with G-LSTM model.The recommendation performance of G-LSTM model is shown in Fig. 1.The MRR of G-LSTM model=0.933, NDCG@2=0.977. From the figure, it can be seen that comparing with the existing model, the new model G-LSTM of this paper is effective and stable to improve the performance in all the indexes.

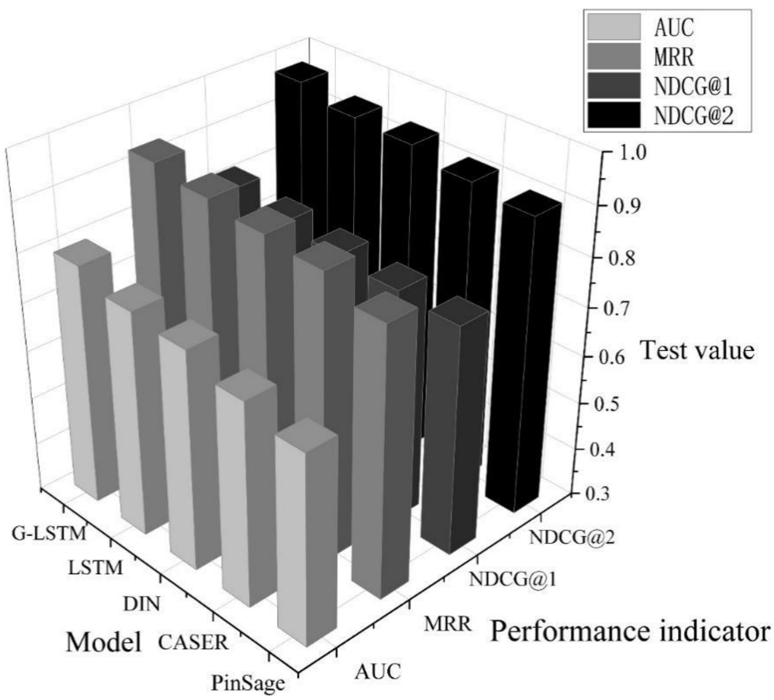

Fig. 1. The LSTM model of the LSTM model

Next, further experiments were conducted to compare the loss function curves of each model, and the model loss function comparison is shown in Figure 2. The model loss is also a judgment criterion for the model's superiority, as can be seen from the figure, the smallest training lossification is found to be the G-LSTM model, and the model loss rate of the G-LSTM model is [1.5, 1.8] when the number of iterations reaches [500, 700], which proves that the accuracy of the G-LSTM model is better than that of the benchmark model.

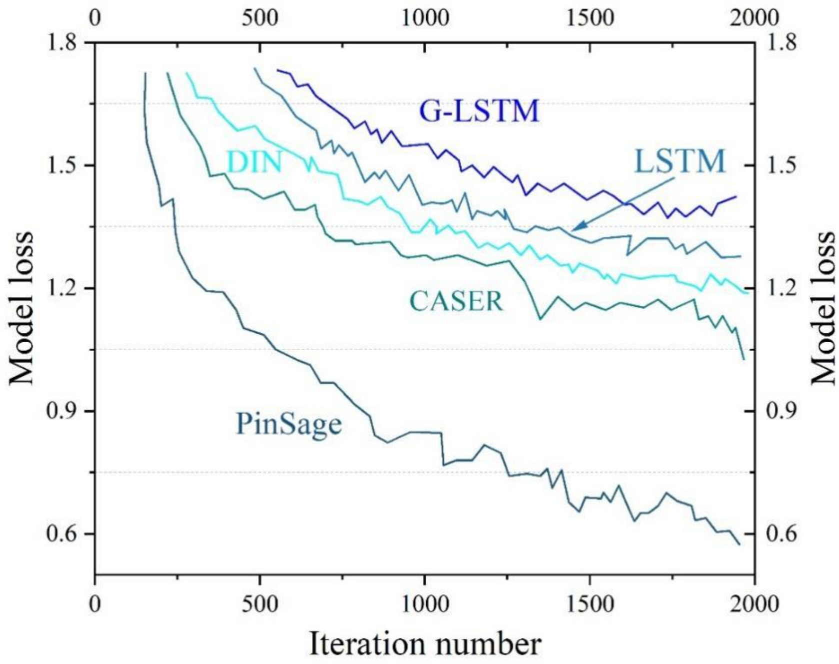

Fig. 2. Comparison of model loss functions

The problem of data sparsity cannot be ignored in recommender systems, and the ability to achieve better results for learners with different sparsity is an important indicator of a recommender system. According to the number of learners' historical interaction behaviors, grouping studies are conducted, in order to eliminate randomness and ensure that each group has a sufficient number of learners. The study is divided into three groups: 0~100, 100~200 and 200~500, and two indicators, NDCG@2 and AUC, are selected for the comparison of average recommendation accuracy calculation. The comparison of teaching resource recommendation performance for learners with different viewing times is shown in Figure 3.

Both NDCG@2 and AUC, G-LSTM achieves effective and stable performance enhancement and improves the recommendation accuracy in different sparsity learner groups, 200~500 interval, Average AUC=0.765, Average NDCG@2=0.922.

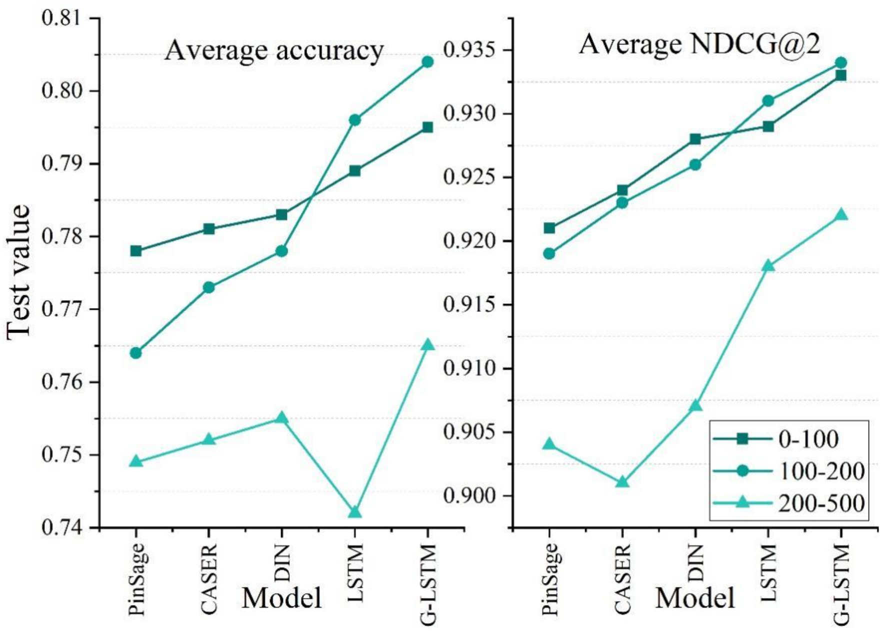

Fig. 3. The teaching resources of different viewing times are recommended

4. Effectiveness of recommended teaching resources for ideological and political theory courses

4.1. *Survey design*

The research is oriented to a university in the Northeast region. The objects of the research are mainly teachers and students specialized in ideology and politics. A total of 600 questionnaires were issued and 585 were retrieved, with a recovery rate of 97.5%. The final summary of the research results, statistical analysis of various types of data, the formation of ideological and political theory course network teaching resources recommended development of the overall program.

The specific questions of this questionnaire are designed as shown in Table 4. There are a total of 6 survey indicators, including teachers' and students' attitudes towards ideological network teaching resources, the quality of ideological network teaching content, the quality of construction, the basic application of teachers and students, the characteristics of ideological network teaching resources and the degree of innovation, and the effect of recommendation.

Table 4. Application situation survey questionnaire

Survey index	Item design
The attitude of teachers and students to network teaching resources	1-Use the basic resources provided by teaching resources and expand resources.
	2-It is necessary to use the use of network teaching resources.
Network teaching resources content	3-Expand resources to adapt to the development of The Times and the need for teaching.
	4-Additional resources should be continued.
Quality of network teaching resource construction	5-Meet professional requirements.
	6-Original resources are higher.
Basic application of teachers and students	7-The frequency of the application of the teaching repository in teaching or learning.
	8-Time to visit the website of the professional teaching resource library.
The characteristics and innovation of teaching resources	9-Using teaching resources can better solve the teaching difficulties.
Recommended effect	10-The content of the teaching resources is high.
	11-Teaching resources are effective in practical teaching or learning activities.

4.2. *Ideological and political network teaching resources construction and application*

4.2.1. Construction of online teaching resources. After investigation, the university has developed 1,032 ideological and political network teaching resources based on the standard of teaching resources construction for ideological majors, with a completion rate of 109.9%. These resources have been successfully uploaded to the shared learning platform of “Digital Learning Center for Ideological and Political Education” and added to various sub-resource libraries, and all kinds of learning contents are open and updated for sharing by different users, with registered users spreading over many provinces in China. The construction projects and the number of network teaching resources of the university are shown in Figure 4.

The school's ideological network teaching resources construction has completed 1032 resource projects, providing students with diverse types and rich content of learning resources.

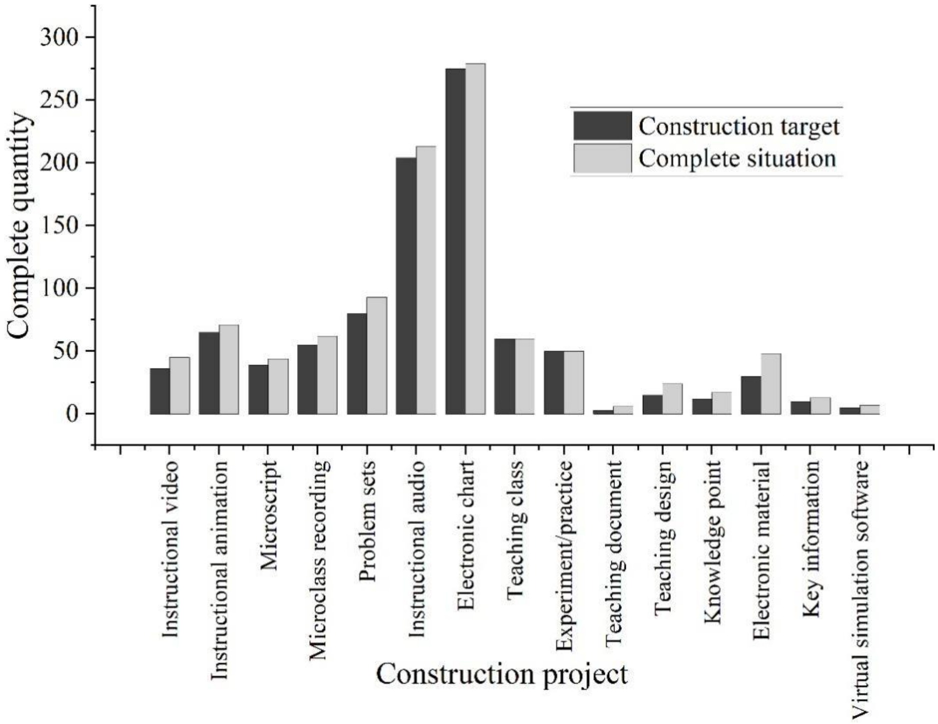

Fig. 4. Network teaching resource construction project and quantity list

4.2.2. Content setting of teaching resources. Teaching resource libraries are diverse in content and facilitate access to lifelong education for all types of users. Whether the contents of teaching resources are perfect and reasonable or not is related to whether teaching resources can maximize their value and promote all kinds of users to receive lifelong education. After the survey, it is found that the designers require teaching resources to be designed according to the boards to facilitate teachers and students to query and learn, and the boards that teachers and students consider the most useful teaching resources and the types of teaching resources that need to be added are shown in Table 5.

The board design of ideological and political network teaching resources is part of its content setting, and the board design is also a reflection of the construction of teaching resources. In the table, course resources are the boards that teachers and students find most useful, accounting for 52.4% and 36.7% respectively.

In terms of the types of ideological network teaching resources, students' favorites are animation resources and virtual simulation resources, accounting for 50.3% and 71.3%, respectively.

Table 5. Network teaching resource content setting

What are the most useful sectors for network teaching resources?			Teachers and students think that the network teaching resource type should be added?		
Plate	Teacher ratio(%)	Student ratio(%)	Audio class resources	Teacher ratio(%)	Student ratio(%)
Professional construction	32.1	18.65	Animation resources	42.2	50.3
Course resources	52.4	36.7	Virtual simulation resources	41.5	71.3
Business case	21.6	5.8	Microclass resources	29.7	48.9
Virtual training	10.3	13.7	Teaching routine resources	55.2	32.0
Training assessment	1.3	6.8	Electronic teaching	36.8	22.4
Information communication	2.6	3.4	Teaching design	18.4	30.5
Composite material	12.9	14.5	Electronic material	12.5	27.3

4.3. *Effectiveness of Recommended Online Teaching Resources*

In order to facilitate the use of teachers and students, every year when new students are enrolled or new teachers are on duty, the school will uniformly organize the registration of users for teachers and students and carry out simple training, so as to achieve the role of teaching resources to assist teachers and students in their learning and work. Therefore the number of users of network teaching resources will realize a certain percentage growth every year.

Students' attitudes towards the effect of recommended ideological and political network teaching resources are shown in Table 6, 71.45% of the students think that the ideological and political network teaching resources are very effective in the actual learning activities. 67.81% of the students very much approve of the network teaching resources that are recommended every time in the ideological and political theory courses.

Table 6. The students' attitude towards the recommendation of teaching resources

Topic \ options	Very fit/%	Coincidence /%	General /%	Discrepancy /%	Very inconsistent /%
Do you think the network teaching resources are updated very quickly?	26.77	37.8	21.04	11.96	2.43
Do you think the quality of the recommended content is high?	67.81	14.24	10.37	1.24	6.34
You think that network teaching resources are very effective in real learning activities	71.45	15.58	10.66	0.96	1.35

Teachers' attitudes toward the effectiveness of the recommended teaching resources on the ideological and political network are shown in Table 7.Teachers' and students' attitudes toward the updating effectiveness of the teaching resource library are generally similar but not identical.15.63% of the teachers think that the updating frequency of the teaching resources on the ideological and political network is very fast.2.87% of the teachers think that the recommendation effectiveness of the teaching resources on the ideological and political network still needs to be improved.

In conclusion, most of the teachers and students think that the frequency of updating the teaching resources library is low, but the quality of the content of each update is high, and most of the students think that the teaching resources library is helpful to their actual learning activities, while the teachers feel that it is average, which may be related to the fact that most of the resources in the library are uploaded by the teachers, and the updated content is not attractive enough for them.

Table 7. Teacher's attitude to resource recommendation

Topic \ options	Very fit/%	Coincidence /%	General /%	Discrepancy /%	Very inconsistent /%
Do you think the network teaching resources are updated very quickly?	15.63	22.66	51.46	9.99	0.26
Do you think the quality of the recommended content is high?	39.71	19.47	30.11	7.84	2.87
You think that network teaching resources are very effective in real learning activities	26.35	31.25	36.05	5.89	0.46

5. Conclusion

This paper analyzes the development of network teaching resources for ideological and political theory courses, selects deep neural network as the recommendation technology of network teaching resources for ideological and political theory courses, and designs the network teaching resources recommendation model based on improved LSTM algorithm. It is applied to teaching practice to analyze the effectiveness of teaching resources recommendation for ideological and political theory classes. Compared with the existing models, the G-LSTM network teaching resources recommendation model in this paper effectively and stably improves the performance in terms of AUC, MRR, NDCG indicators.The MRR of the G-LSTM model=0.933, NDCG@2=0.977. The model loss function curve proves that the accuracy of the G-LSTM model is better than the benchmark model. To carry out the actual ideological and political theory class as a teaching experiment, the statistical survey shows that the ideological and political network teaching resources construction project is rich, the content of teaching resources is sufficient, and the effect of network teaching resources updating and recommendation is good and effective.

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